Journal of Cleaner Production 217 (2019) 742–756

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Comprehensive model of energy, environmental impacts and economic in rice milling factories by coupling adaptive neuro-fuzzy inference system and life cycle assessment

Ashkan Nabavi-Pelesaraei [a, b, *, 1, 2, 3], Shahin Rafiee [a, **], Seyed Saeid Mohtasebi [a], Homa Hosseinzadeh-Bandbafha [a], Kwok-wing Chau [c]

[a] Department of Agricultural Machinery Engineering, Faculty of Agricultural Engineering and Technology, University of Tehran, Karaj, Iran
[b] Coordination Affairs Expert, Management of Fruit and Vegetables Organizations, Tehran Municipality, Tehran, Iran
[c] Department of Civil and Environmental Engineering, Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

ARTICLE INFO

Article history:
Received 25 September 2018
Received in revised form
15 January 2019
Accepted 18 January 2019
Available online 29 January 2019

Keywords:
Environmental impact assessment
Energy
Milling factory
Multi-level adaptive neuro-fuzzy
Rice

ABSTRACT

The increasing energy demand, limited fossil fuel resources and effects of climate change, lead to problems with regard to sustainability of production in food industry. Hence, this article aims to provide energy, economic and environmental overview about the production of white rice in milling factories of Guilan province, Iran. Information are collected during factory site visits as well as interviews with staff of 60 milling factories. Besides, required data about the background system is extracted from Ecoinvent 3.3 databases. Energy analysis indicates that in these milling factories, 68,178.31 MJ per ton input paddy to millings is used and 68,178.31 MJ per ton input paddy of energy is generated. Life cycle assessment is used in this work. Results show that the natural gas (background processes of natural gas extraction, production and direct combustion) has a key role in all impacts category in this study. The reason for this is inefficiency of drying in milling factories. The economic analysis shows net profit of 47.37 ($ per ton input paddy) and the total cost of 294.21 ($ per ton input paddy). Besides, social cost for emission of production in these factories is 30.99 ($ per ton input paddy). A hybrid learning algorithm is employed in developing an adaptive neuro-fuzzy inference system model for predicting economic profit, output energy and global warning in milling factories. Coefficients of determination in forecasting output energy, economic profit and global warning are estimated to be 0.911, 0.978 and 0.964, respectively. Results demonstrate the usefulness of multi-level adaptive neuro-fuzzy inference system to management level for long-term planning in predicting various environmental, energy and economic indices of large-scale food production systems.

1. Introduction

The food industry is a large energy user and is, in fact, one of the world's largest industries (Silalertruksa and Gheewala, 2013). Energy takes a dominant position in every step of the food industry including crops and livestock production, processing, packaging, distributing, storing, preparing, serving and disposing steps of food products (Xu and Szmerekovsky, 2017). The food industry that accounts for 30% of global energy consumption has been introduced as a sector of the industry that has a high potential for energy savings (Xu and Szmerekovsky, 2017). Therefore, study of the process of consuming and producing energy in these industries is necessary to find the sectors that lead to energy savings. In addition, the significant increase in industrial food production due to the escalated energy consumption results in a tremendous rise of emission of greenhouse gases (GHGs). It in turn leads to extension of the phenomenon global warning potential (GWP) that is perchance the most serious issue that humankind faces in the current situation (Roy et al., 2009). Therefore, it is essential to study

* Corresponding author. Department of Agricultural Machinery Engineering, Faculty of Agricultural Engineering and Technology, University of Tehran, Karaj, Iran.
** Corresponding author.
E-mail addresses: ashkan.nabavi@yahoo.com, ashkan.nabavi@ut.ac.ir (A. Nabavi-Pelesaraei), shahinrafiee@ut.ac.ir (S. Rafiee).
[1] https://www.researchgate.net/profile/Ashkan_Nabavi-Pelesaraei.
[2] http://orcid.org/0000-0003-2823-6616.
[3] https://scholar.google.com/citations?user=JQNGIIIAAAAJ&hl=en.

https://doi.org/10.1016/j.jclepro.2019.01.228
0959-6526/

the coexistence of environmental and energy impacts in the food industry for successful management of sustainable production.

Energy management and life cycle assessment (LCA) are both very important tools to enhance the sustainable production in industries including food industry (Chauhan et al., 2011). LCA is a key approach to undertake environmental impact assessment of services and products. The meaning of LCA approach was introduced in 1990s and it comprised the scope, costs and endeavors needed when an LCA study was performed (Arzoumanidis et al., 2017). On the other hand, energy management of an industry is an effective method for energy consumption to minimize its cost (Chauhan et al., 2011). In the last decade, due to the large growth of energy use, energy demand management played a significant role in accomplishing appropriate resources planning, environmental protection and economic success, as well as economic development. Hence, different methods have been developed for prediction and modeling of future energy demands accurately (Suganthi and Samuel, 2012). Yet, it is difficult to implement appropriate energy modeling due to rapid development of technology, economy, government decisions, etc. (Yu et al., 2012). The adaptive neuro-fuzzy inference system (ANFIS) (Jang, 1993) is a powerful technique of energy modeling and has outstanding learning and forecasting abilities. It is basically a hybrid intelligent system, which renders it an efficient tool in addressing uncertainties in any system. Given this important feature, it has been employed to solve different problems (Chen et al., 2015; Naji et al., 2016). In energy management, in addition to the topic of energy demand analysis, as well as modeling and predicting energy consumption, Cumulative Exergy Demand (CExD) analysis is another significant tool, which can generate a more efficient system or process with minimized loss or degradation of exergy ("quality" of energy) (Peters et al., 2014).

Rice (*Oryza sativa L.*) is the staple food and an important nutritional source of protein to more than 3 billion people globally, particularly in Asia (Thanawong et al., 2014). Paddy (rice with husk) mills (a process that removes the husk and part of the bran by various steps as drying, winnowing, whiting, etc.) produce edible rice, and hence, milling is a key step in post-production of rice (Kumar et al., 2016). Considering the importance and expansion of white rice consumption, especially nowadays when the Asian and Latin American countries are expanding to meet the increasing demand for food resulting from human population growth, rice-milling industry is one of the leading industries in the world (Kumar et al., 2016). With regard to the issue of food security and the development of sustainable production, various studies have been carried out on environmental, energy and economic assessments of converting paddy to white rice chain in different parts of the world (Table 1).

Like many Asian countries, rice is the staple food in Iran. For Iranian consumers, the most important consideration in selecting rice is the quality of cooked rice. Rice cultivation is made in fifteen Iranian provinces, with total cultivation area more than 600,000 ha. Yet, more than eighty percent of rice cultivation area is located at Mazandaran (with 265,000 ha of rice cultivation area) and Guilan (with 230,000 ha of rice cultivation area), which are two northern provinces. Rice production in Iran increased from 0.6 million ton in the late 1960s to 2.3 million ton in 2014 (FAO, 2014).

Bearing in mind the importance of rice production in Iran, needs are felt for higher eco-efficiency and more attention to the consumption of inputs in terms of environmental performance in converting paddy to white rice chain for attaining sustainable production. However, in various researches in Iran, rice production has been considered in the field in terms of sustainable agricultural principles. Yet, there is no comprehensive study on the sustainability of production in the post-rice production stages (milling) in rice production of Iran. Therefore, an investigation is needed to assess the environmental, energy, and economic aspects of the production chain of rice from the arrival of the paddy to the factory to produce white rice (packaged) by tools like energy management and LCA. Finally, using fuzzy-neural logic, a comprehensive model for predicting the amount of outputs (environmental, energy, and economic aspects) to identify opportunities and limitations.

Therefore, this paper aims to depict the life cycle of converting paddy to white rice chain in milling step in Guilan province, Iran from the following perspectives: 1) energy flow and exergy; 2) environmental impacts, and 3) economic indicators (indicators relating to profit and cost, as well as indicators related to the cost of environmental emissions). It aims to identify: 1) energy use pattern and energy indexes, 2) environmental indicators of converting paddy to white rice chain at milling stage of the production chain, 2) environmental hotspot of converting paddy to white rice chain at milling stage of production chain, and (3) economic profit of converting paddy to white rice. It also provides a comprehensive model using ANFIS for forecasting and modeling of energy (yield), GWP and economic profit in converting paddy to white rice to help attaining goals of sustainable production in agriculture and food industries.

2. Methods and materials

2.1. Sampling design

This investigation is a follow-up work of our previous study (Nabavi-Pelesaraei et al., 2017) that encompasses "comprehensive model of energy, environmental impact and economics in milling factories by integrating adaptive neuro-fuzzy inference system and life cycle assessment ". The location of Guilan province is at longitude between 48° 53′ and 50° 34′ E and at latitude between 36° 34′ and 38° 27′ N (Nabavi-Pelesaraei et al., 2017). Being located at the Southwest coast of the Caspian Sea, its temperate and humid climate (average annual precipitation around 1850 mm) is quite distinguished when compared to other parts of Iran, which are in general dry and hot (average annual precipitation in Iran around 236 mm) (Fig. 1). With ample supply of water, high relative humidity and fertile lands, Guilan province becomes a key rice producer in Iran, furnishing 35.81% of the total area of paddy fields in Iran. For this reason, a number of milling factories are located in this province. Therefore, information employed in this investigation are gleaned from 60 milling factories through direct interviews with factory workers and specialists. Regarding the uniformity of the standard for the establishment of milling factories, there is a relative similarity of consumption in the factories, which are largely repeatable.

Before *the* collocation of the initial data, the entailed sample size is estimated by using the following formula (Cochran, 1977):

$$n = \frac{\frac{z^2pq}{d^2}}{1 + \frac{1}{N}\left(\frac{z^2pq}{d^2} - 1\right)} \quad (1)$$

where d denotes the allowable error ratio deviation from the mean population (= 0.05), p is the computed proportion of an attribute within the population (= 0.5), q is 1-p (= 0.5), n is the entailed sample size, z is the reliability coefficient (= 1.96 at 95% confidence level), and N is the ratio of the number of milling factories to the target population.

2.2. Energy flow in white rice producing of milling factories

The first step to determine energy use pattern and study energy

Table 1
Summary of previous studies conducted on environmental, energy and economic assessment for converting paddy into white rice chain.

Previous study	Range of study	Assessment type	Remarks
Kasmaprapruet et al. (2009)	Farm to milled rice	Environmental (by LCA)	• 2.93 kg $CO_{2\ eq.}$ per kg of milled rice. • 95% of the GHG emissions was related to the farm stage arising from methane emissions in paddy rice production. • 3.19 g $SO_{2\ eq.}$ per kg of milled rice. • Drying process had a share equal to 42% in Acidification. • Drying process had a share equal to 17% in eutrophication.
Blengini and Busto (2009)	Farm to milled rice	Environmental (by LCA) and energy	• 2.9 kg $CO_{2\ eq.}$ per kg of white milled rice • A primary energy consumption of 17.8 MJ per kg of white milled rice
Pishgar-Komleh et al. (2011)	Farm	Energy and economic	• 39,333 MJ ha^{-1} with energy productivity. • Energy productivity and energy ratio were 0.09 and 1.53 kg MJ^{-1}, respectively. • Benefit-Cost ratio, net return, gross return and total cost of production were 1.29, 940 \$ ha^{-1}, 1642 \$ ha^{-1} and 3156 \$ ha^{-1}, respectively. • Large farms (with more than 1 ha) had better economic and energy use performance.
Thanawong et al. (2014)	Farm to milled rice	Environmental	Amount of GWP_{100} of dry-season irrigated systems, wet-season irrigated systems and wet-season rainfed systems were 5.55, 4.87 and 2.97 kg $CO_{2\ eq.}$ per kg of rice, respectively.
Firouzi et al. (2017)	Milling factory	Energy	Thermal energy use efficiency was estimated to be 38.8% and 26.3% for conventional industrial batch-type bed dryer (IBBD) and industrial horizontal rotary dryer (IHRD), respectively
Taheri-Rad et al. (2017)	Farm	Energy molding (artificial neural network (ANN) and Cobb-Douglas (CD))	(8–25–1) topology was the best model in paddy cultivars based on result comparison.

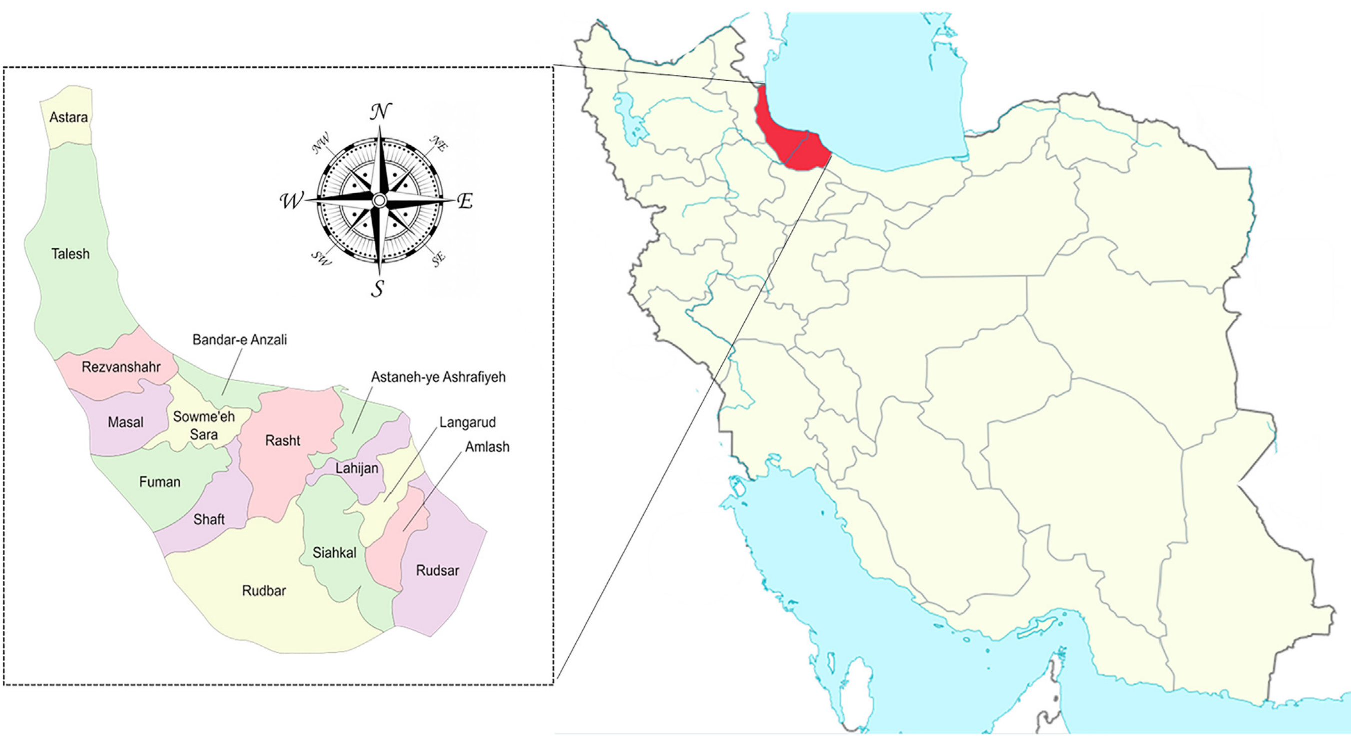

Fig. 1. Location of the studied area in north Iran.

flow in a production system is to compute input and output energy values. The energy equivalent can be determined by using the standard coefficient of energy conversion. Amounts of equivalent energy can be determined by direct multiplication of standard coefficients to these input and output amounts (Mousavi-Avval et al., 2011). In this milling factory study, fossil fuels (natural gas), machinery and equipment, electricity, transportation, human labor and nylon are taken as inputs whilst white rice is considered as the output. Standard coefficients of input and output energy are shown in Table 2.

Four energy indices are employed to compare production system from energy viewpoint for milling factories and conversion of paddy to white rice. They are listed as follows: 1) net energy gain (NEG) denoting the difference between the gross generated energy output and the total input energies; 2) specific energy (SE) denoting the energy consumption per mass for the product; 3) energy productivity (EP) denoting the inverse of SE which is the generated product amount for each unit of input energy; and 4) energy ratio (ER) denoting the ratio of the output energy to the total direct and indirect input energies (Mandal et al., 2015).

2.2.1. Uncertainty analysis

Although uncertainty in engineering issues can be created from different sources, this uncertainty is generally divided into two categories including: a) Intrinsic uncertainty (Aleatory) b) Cognitive uncertainty (Epistemic). Intrinsic uncertainties actually

Table 2
Energy coefficients and inputs/output energy in various operations of milling factories.

Item	Unit	Energy equivalent (MJ unit^{-1})	Reference
A. Inputs			
1. Human labor	h	1.96	Hosseinzadeh-Bandbafha et al. (2018)
2. Machinery	kg	142.7	Yousefinejad-Ostadkelayeh (2015)
3. Electricity	kWh	11.93	Nabavi-Pelesarei et al. (2016)
4. Natural gas	m^3	49.5	Nabavi-Pelesaraei et al. (2017)
5. Nylon	kg	90	Canakci and Akinci (2006)
6. Transportation	t.km	6.1	Jalali-Sefat (2013)
B. Output			
1. White rice	kg	17	Pishgar-Komleh et al. (2011)

represent the natural randomness of phenomena, but cognitive uncertainties result from a lack of information and knowledge. The reason for the division of uncertainties into these two categories is that the defect in the data itself can be considered as a non-physical auxiliary accidental variable. This variable includes information that is gathered from more information or based on advanced engineering concepts. More importantly, these auxiliary variables define the statistical dependence, which has certain uncertainties (Paté-Cornell, 1996).

Results of uncertainty analysis are effective to select appropriate model method. In this study, the energy consumer inputs in milling factories are considered as uncertainty maker resources and the normal standard deviation is applied as a method for uncertainty analysis of individual measurement (Bland and Altman, 1996).

$$S = \sqrt{\frac{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2}{n-1}} \tag{2}$$

$$S_n = \frac{S}{\sqrt{n}} \tag{3}$$

where x_i is the amount of inputs in each factory; $\overline{X}$ is the average of input energy; n is the ratio of the number of milling factories to the target population; S is standard deviation and S_n is the normal standard deviation.

2.3. LCA methodology

Agri-food production sector has been generating many environmental hazards such as waste generation, emission generation, land degradation, resource depletion (Beccali et al., 2009). LCA is a feasible tool to perform environmental impact assessment for different production systems (Kucukvar et al., 2014). LCA focuses on the environmental effects of a product or service. When making choice amongst different options, the decision is determined by composing LCA results with various aspects including technical feasibility, economic efficiency, social implications, costs, etc. Other supplementary analysis, such as life cycle costing, is implemented to appraise these aspects (Jolliet et al., 2003). Based on ISO norms 14040, LCA comprises of four basic steps: (i) definition of scope and goals, the purpose of which is to identify the aims, system boundaries and functional unit; (ii) Life Cycle Inventory (LCI), which includes a detailed compilation of all environmental inputs (energies and materials) as well as outputs (solid, water and air emissions) throughout various life cycle stages; (iii) Life Cycle Impact Assessment (LCIA) whose objective is to quantify the comparative significance of various environmental burdens identified in LCI via analyzing their impacts on specific environmental outcomes; and (iv) result interpretation (ISO, 2006).

2.3.1. Goals, system boundary and functional unit

The definition of goals is the first step of LCA (Guinée, 2001). This study aims to undertake measurement of GWP impacts category as well as other environmental impacts with energy consumption to provide a model to predict rate GWP impacts category in life cycle for converting paddy to white rice in milling factories.

The system boundary setting in LCA is a critical process since it affects outcome largely. System boundary defines production steps to be included as well as those to be excluded in the assessment (European Commission, 2010). A too broad system boundary set may include impacts produced by processes out of scope of the study whilst a too narrow system boundary set may leave out some significant impacts of interest (Blengini and Busto, 2009). In our study, all inputs from input gate to output gate of milling factories are covered in system boundary. It in general covers all operations performed within the system boundary including: transportation, drying, winnowing, de-stoner, de-husking, paddy separator, whiting, packing. Fig. 2 indicates a schematic diagram of the system boundary in milling factories of Guilan province.

As an important concept in LCA, Functional Unit (FU) denotes the unit to represent inventory data (Kylili et al., 2016). It is not a ratio, yet has to be additive and quantifiable. According to various studies of LCA in agri-food production, the conventional FU is the mass, so one ton input paddy to millings is adopted as the FU here.

2.3.2. Life Cycle Inventory

The second step of LCA analysis is Life Cycle Inventory (LCI), which determines the quantity of input consumption for each unit of FU (Guinée, 2002). In this way, pollutant emissions to soil, air, and water over each process throughout the product life cycle are determined (ISO, 2006). Two datasets are employed for accomplishing LCI in this study, namely, dataset from the *foreground system* and dataset related to the *background system*. The dataset from the *foreground system* includes all data of converting paddy to white rice in milling factories, which are gleaned from questionnaires and direct inquiries. The second dataset comprises data regarding consumable input production as well as emissions of natural gas combustion obtained from Ecoinvent 3.3 (Ecoinvent Database, 2013).

2.3.3. Life Cycle Impact Assessment

Life Cycle Impact Assessment (LCIA) is the third step of a LCA, based on International Organization for Standardization (ISO, 2006), following data collection on substance emissions and raw material extractions pertinent to life cycle of the product. Several methods exist for LCIA, including CML, EPS2000 and Eco-indicator 99 methods, etc. CML method (Heijungs et al., 1992; Sabzevari et al., 2015) is employed in this study. Furthermore, the adopted impact categories comprise GWP, Marine Aquatic Ecotoxicity (ME) potential, Freshwater Aquatic Ecotoxicity (FE) potential, Human Toxicity (HT) potential, Ozone Layer Depletion (OLD) potential,

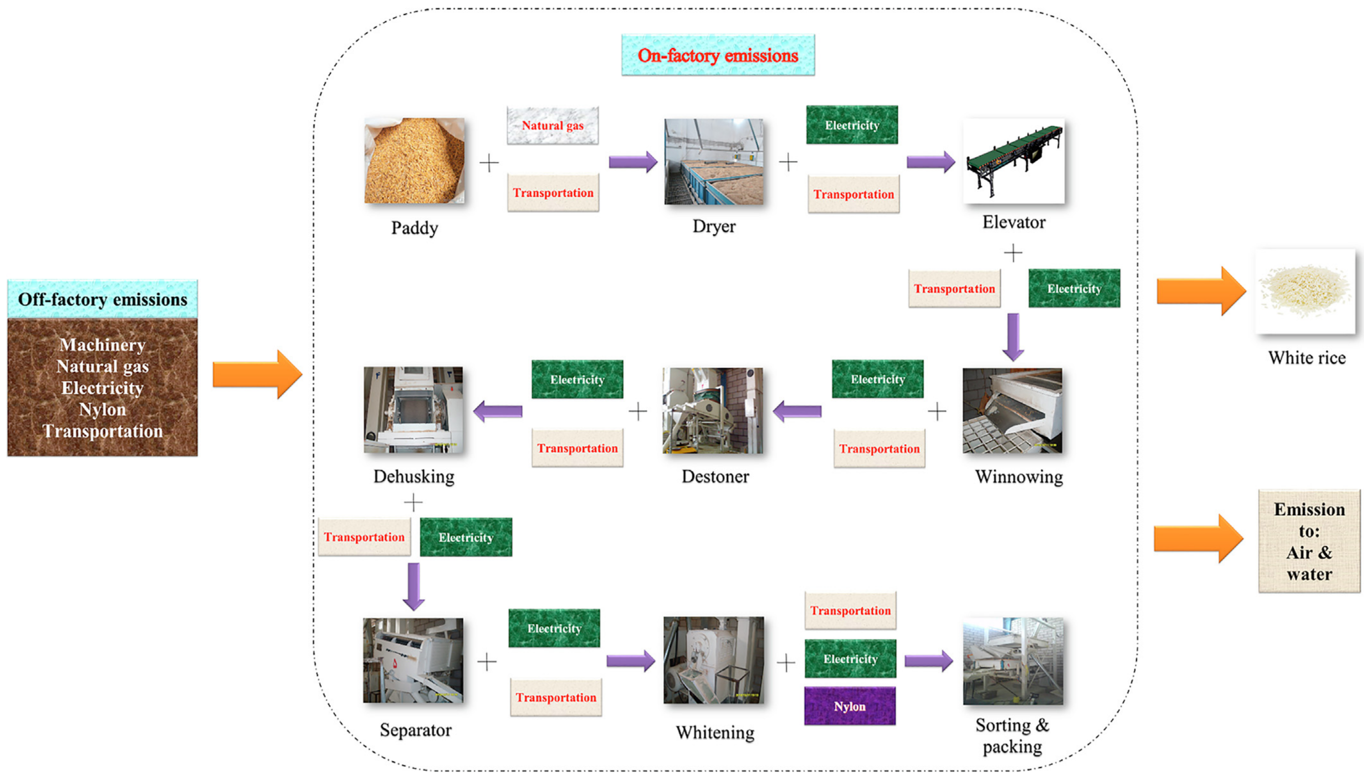

Fig. 2. System boundaries of white rice production in milling factories of Guilan province, Iran.

Eutrophication (EP) potential, Photochemical Oxidation (PO) potential, Terrestrial Ecotoxicity (TE) potential, Abiotic Depletion (AD) potential and Acidification (AC) potential under a time period of 100 years.

2.4. CExD approach

Exergy, being a unique methodology and indicator, is employed to evaluate the quality of energy sources under LCA. Extended Exergy Accounting (ExA) concentrates on the analysis of energy system plan and the recognition of major thermodynamic irreversibility resources, although irreversibility resulted from the use of renewable or non-renewable resources cannot be distinguished by this method (Kostowski et al., 2014). Nevertheless, the ever expanding usages of renewable energy recently in various product systems elevated the significance of life cycle analysis (Gibon et al., 2015). As such, verification of ExA should be undertaken with a life cycle. It is because the reduction of internal irreversibility within a specific system may not necessarily follow with a reduction of its entailed main energy resources (Rocco et al., 2014). A definition of CExD is the total entailed amount of main exergy for the production of a service or a product. It takes into account both renewable as well as non-renewable main energy resources, including mineral, metals, water and consumption, etc. (Bösch et al., 2007).

2.5. Economic analysis of white rice producing of milling factories

Finally, the economic analysis of converting paddy to white rice of milling factories is investigated. For this purpose, fixed cost of converting paddy to white rice, variable cost of converting paddy to white rice chain, total cost of converting paddy to white rice chain, total conversion of paddy to white rice chain revenue and net profit are calculated. The total cost of converting paddy to white rice in milling factories comprises both variable and fixed costs. The variable costs include costs of used materials such as electricity, natural gas, and others in addition to operation costs whilst the fixed costs are mainly rental cost of 1 ton input paddy (TIP). Data costs are computed for 1TIP and employed to determine various economic indices. The net profit is computed by subtraction of the total production cost from the total revenue for 1TIP of milling processing.

$$\textit{Total cost of converting paddy to white rice chain } (\$\ 1TIP^{-1}) = \textit{Variable cost of production}(\$\ 1TIP^{-1}) + \textit{Fixed cost of converting paddy to white rice chain } (\$\ 1TIP^{-1}) \quad (4)$$

$$\textit{Net profit } (\$\ 1TIP^{-1}) = \textit{Total conversion of paddy to white rice chain revenue } (\$\ 1TIP^{-1}) \textit{ - Total cost of converting paddy to white rice chain } (\$\ 1TIP^{-1}) \quad (5)$$

Economic analysis of potential climate change effects is usually based on welfare economics (Foley et al., 2013). According to Stoellinger et al. (2016), the social cost of carbon (SCC) is an equivalent economic value of the additional impact resulted from the reduction of one ton of carbon (expressed in carbon dioxide) or emission under a specific spatial-temporal dimension. The higher the SCC value, the prevention of a larger damage is accomplished when decreased GHG emissions are made. Under such case, it becomes optimal to invest more in order to reduce such emissions, when all other conditions remain the same (Van den Bergh and Botzen, 2015). Based on the social welfare criterion and economic efficiency, it is better to bear the damages resulted from the emission if the costs of diminishing CO_2 emission are higher than the SCC. It can be noted that the derivation of an appropriate value of the SCC is very significant since the government body will come up with a drastically different climate policy under different SCC values. Since 1996, various SCC values have been proposed by different researchers. In this research, the social cost of emissions is

estimated by using the standard coefficient. Table 3 shows cost of environmental emissions in (\$ $1TIP^{-1}$ of $CO_{2\,eq.}$) and other emission indices.

2.6. ANFIS

The concept of Fuzzy Logic (FL) is well acknowledged because of its capability of transition from linguistic terms into mathematical symbols since Zedeh (Nikravesh et al., 2003). FL employs specific if-then rules and provides a novel way to realize a physical process under qualitative or uncertain terms instead of applying crisp values. Yet, it is essential to obtain a precise and thorough view regarding the specific problem (Karkevandi-Talkhooncheh et al., 2017). Owing to various reasons such as diversity in human expert opinions, lack of knowledge or occurrence of errors, proper outcomes may not be resulted by simulating a problem with the FL concept solely (Safari et al., 2014). However, alternative approaches such as artificial neural networks (ANNs) can be employed owing to their data-driven supervised learning capability. ANFIS combines the power of both ANN and FL techniques. According to Jang (1993), the hybrid process is performed via introducing membership functions (MFs) which are fine-tuned and optimized via the capability of ANNs and fuzzy if-then rules under a specific architecture termed Fuzzy Inference System (FIS).

In different researches, two kinds of FISs, namely, Takagi-Sugeno-Kang (TSK) and Mamdani, were employed (Singh et al., 2012). TSK type FIS performs by generating rules according to input and output data (Kostowski et al., 2014). Mamdani type FIS runs by using intelligent if-then rules on the basis of expert statements, which often result in imprecision and obscurity. Owing to TSK FIS's higher capability in handling nonlinear relationships among input and output parameters, it is employed in this study.

A typical ANFIS comprises five neuron layers. Neurons in each layer belong to the same function group. Fig. 3 shows a typical ANFIS structure including five layers. In the first layer, each neuron possesses membership functions of a linguistic attribute. In the second layer, each node, by employing the prod or min operator, computes the firing strength for a rule. The third layer presents outputs called normalized firing strengths. In this layer, each neuron computes the ratio between the firing strength of the rule and the summation of firing strengths of all rules. Each node in the fourth layer computes a parameter function of the output from the third layer. In the fifth layer, there is only one output node, in which all incoming signals are aggregated to produce the overall output (Mousavi-Avval et al., 2017).

Nevertheless, a limitation is usually imposed for applying ANFIS, namely, the maximum number of ANFIS inputs is five, because the computational time increases exponentially with the number of rules. In order to reduce the number of criteria, it might be recommended to use methods such as data clustering or principal component analysis (PCA). In data clustering technique, data are clustered into smaller groups by their behavior in order to attain a concise and better system representation (Mousavi-Avval et al., 2017). In this study, clustering approach is employed to categorize the six input parameters into three divisions. Accordingly, four ANFIS sub-networks are developed in this model, as shown in Fig. 4.

Owing to the excessive logic of behavior in inputs by manufacturers, from zero to one and not covering all the parameters in definitive modeling and attaining optimal model (with respect to three objectives), the fuzzy-neural method is used. On the other hand, the purpose of this study is to study and model energy flow, environmental impacts and economic benefits of factories in the present situation to identify the opportunities and limitations, which can be determined by the fuzzy model.

For validation of the selected models, several performance metrics, namely, RMSE, R^2 and MAPE between real observations and predicted ANFIS results, are used:

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}}\sum_{i}^{n}(t_i - z_i)^2} \tag{6}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(t_i - z_i)^2}{\sum_{i=1}^{n} t_i^2}\right) \tag{7}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{|t_i - z_i|}{z_i}\right) \tag{8}$$

where n is the total number of points within the dataset; z_i and t_i are the observed and predicted results, respectively.

The analysis on energy indices and patterns of energy consumption are undertaken by employing Excel 2016 spreadsheets. SimaPro V8.0.3.14 is used to perform CExD and LCA and analysis. For performing ANFIS analysis, Matlab (R2016b) software package is employed, into which all input and output data in milling factories are entered.

Table 3
Emission-Cost coefficients for background emission indices in milling process (Ministry of Energy of the Islamic Republic of Iran, 2012).

Emission index	Unit	Emission equivalent for electricity consumption (unit per kWh)	Emission equivalent for natural gas consumption (unit per m^3)	Social cost for emission index (\$ $unit^{-1}$)
1. NO_X	kg NO_X eq.	2.792×10^{-3}	3.639×10^{-3}	0.6
2. SO_2	kg SO_2 eq.	3.119×10^{-3}	0.0042×10^{-3}	1.825
3. CO	kg CO eq.	0.653×10^{-3}	0.669×10^{-3}	0.187
4. SPM	kg SPM eq.	0.135×10^{-3}	0.188×10^{-3}	4.3
5. CO_2	kg CO_2 eq.	716.18×10^{-3}	1929.20×10^{-3}	0.01
6. CH_4	kg CH_4 eq.	0.018×10^{-3}	0.130×10^{-3}	0.21
7. N_2O	kg N_2O eq.	0.003×10^{-3}	0.0036×10^{-3}	4.58

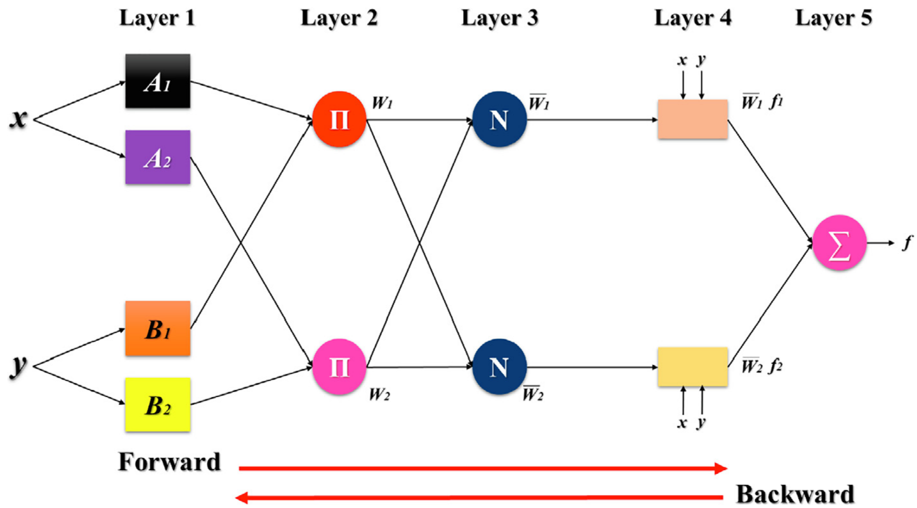

Fig. 3. Architecture of ANFIS model.

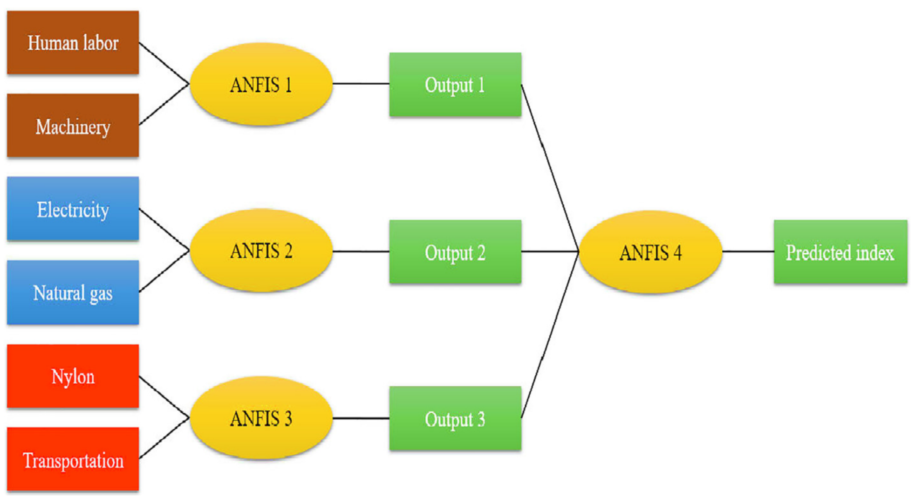

Fig. 4. Two level ANFIS structure to predict output energy, environmental impacts and economical profit of milling factories.

3. Results and discussions

3.1. Input-output energy flow

Amount and equivalent energy inputs and white rice in milling factories based on 1TIP are listed in Table 4. Results show that the total amount of input energies in milling factories is 68, 178.31 MJ 1TIP^{-1}. This value of energy consumption leads to the generation of 11,894.64 MJ 1TIP^{-1} equivalent energy conversion of paddy to white rice in milling factories. The major share of energy consumption in these factories is estimated to be 8662.07 MJ 1TIP^{-1} (96.43%) for natural gas use.

The moisture content of paddy ranges from 25 to 28% at time of harvesting (Sangdao et al., 2010), which is much higher than the suitable moisture content for paddy husking or storage of 14% or so (Zecchi and Gerla, 2007). Therefore, it is necessary to reduce the moisture content of rice by heat drying. In the process of drying paddy, scientific and technical principles are endeavored to raise the efficiency in converting paddy to white rice for longer and better keeping of the rice in warehouse (Jafari et al., 2018). Moreover, paddy drying process accounting for all energy consumption to produce milled rice in the studied case is via natural gas. As such, changing in type and amount of energy consumption (natural gas) of the paddy drying process is at the top of the list for attaining higher energy efficiency in milling factories.

At present, most rice mills in Iran employ conventional low efficient paddy drying method. When the moisture of most grain is not removed, significant volume of hot air energy is lost to the environment. So, the first step in reducing the fuel consumption (natural gas) of rice dryers is the change in the type of dryer. Though according to Firouzi et al. (2017), no ideal drying technique exists to dry paddy since every method has both pros and cons, but literature review shows that significant efforts had been undertaken to determine efficient drying techniques to enhance rice milling quality in energy term (Nimmol and Devahastin, 2010; Sarker et al., 2014). In addition to changing the type of dryers, changing the type of energy consumption can also be a suitable approach to reduce natural gas consumption as an unstable fossil energy source. Renewable energies can play a key role to meet energy demand (Mustayen et al., 2014) and using them as a source of energy greatly reduces the consumption of natural gas. Solar energy can be used as solar PV, solar thermal for drying paddy since it is reliable and inexpensive. Besides, rice husks, a crop biomass, can be an inexpensive renewable energy source with calorific value

Table 4
Energy inputs and output in milling factories based on 1TIP.

Items (unit)	Unit per 1TIP	Energy consumption per 1TIP	Percentages (%)
A. Inputs			
1. Human labor (h)	28.63	56.11	0.08
2. Machinery (kg)	0.99	141.08	0.21
3. Electricity (kWh)	75.64	907.64	1.33
4. Natural gas (m^3)	1328.10	65741.02	96.43
5. Nylon (kg)	13.97	1257.23	1.84
6. Transportation (t.km)	12.33	75.23	0.11
Total energy input	–	68178.31	100
B. Output			
1. White rice (kg)	699.68	11894.64	–

of 11–15.3 MJ kg^{-1} (Quispe et al., 2017). However, the use of these types of energy has not yet been used commercially and economically for drying machines in the area, and there is no information on its use and its effect on the performance of white rice. It is recommended that feasibility studies be considered in future studies and results will be compared with the model presented in this study.

Goyal et al. (2008) reported that energy uses in post-harvest rice processing operations in huller mill, mini rice mill, raw rice mill and parboiled rice mill were 15.65, 14.42, 36.29 and 923.92 kWh ton^{-1}, respectively. It was also reported that operation-wise energy use required are as follows: bagging and weighing 1.67 kWh ton^{-1}, milling 39.75 kWh ton^{-1}, drying 271.58 kWh ton^{-1}, steaming 75.16 kWh ton^{-1}, soaking 527.21 kWh ton^{-1} and pre-parboiling cleaning 1.34 kWh ton^{-1}. According to Roomi et al. (2007), specific energy required to produce one ton of rice in semi-modern and modern rice mills were reported as follows: 42.84 kWh ton^{-1} and 41.10 kWh ton^{-1} of electrical energy, 917 MJ ton^{-1} and 1092 MJ ton^{-1} for thermal energy requirement for drying and parboiling. In another study on milling process, energy consumptions are computed as 0.09288, 0.03816 and 0.02988 MJ kg^{-1} for 10, 5 and 2% milling, respectively. It showed that energy use were dependent on the milling degree so that the energy consumption increases with the milling degree (Roy et al., 2009). Moreover, Roy et al. (2005) reported that, for parboiled rice, energy use in the milling process was 0.09468 MJ kg^{-1}. Comparing results of this study with the above-mentioned studies indicates that there is a very high energy consumption for milling factories in Iran. Unlike many rice-producing areas, which due to the high cost of energy, involve the use of more efficient dryers such as industrial horizontal rotary dryer, dryers that are commonly used in the studied milling factories here are conventional industrial batch-type bed dryer. A factory that had industrial horizontal rotary and conventional industrial batch-type bed dryer was studied. It was observed that drying with a temperature of 50 °C in an industrial horizontal rotary dryer with a capacity of 3–4 tons per 20 h and taking into account the application of temperature control equipment, the energy consumption in the industrial horizontal rotary dryer is about 40% lower than conventional industrial batch-type bed dryer. Hence, replacing the lying dryers to standing is very important to reduce energy consumption. In the next step, attempt should be made to reduce consumption of natural gas by replacing it with sustainable energy. However, owing to the high availability and low price of natural gas, it is currently in high consumption. Yet, according to the principles of sustainable production, its consumption should be minimized to reach the global standards of energy consumption for drying paddy in north Iran.

Table 5 shows different energy indexes in milling factories. It can be observed that the amount of energy ratio in milling factories is 0.17. Nabavi-Pelesaraei et al. (2014) found that, for paddy cultivation, the energy ratio was 1.29, which was higher than the value computed in the milling factories. Moreover, in nectarine production, the energy ratio was computed as 1.36 in Mazandaran province of Iran (Qasemi-Kordkheili and Nabavi-Pelesaraei, 2014). The comparison of results indicates that the energy performance of milling factories in Guilan province of Iran is lower than that of tea factories.

Results of uncertainty analysis are demonstrated in Table 6 based on 1 TIP, which indicate that uncertainty percentages of consumption are between 6.77% and 48.74% with different inputs. Natural gas and electricity have the highest amount of uncertainty. The lack of appropriate pattern and low price of these inputs are the main reasons for this uncertainty. Obviously, the behavior of energy consumption cannot be modeled by classic (certainty) models based on classic normal distribution. As can be seen in Table 6, the high rates of uncertainty in input consumption are the main reasons for inadequacy of classic (certainty) models in this study. Since there is considerable uncertainty of energy consumption in milling processes among all sites, it seems that the operation and energy management could also be significantly improved to reduce energy inputs and environmental impacts caused by energy consumption.

Ways that can be used to manage energy consumption in milling include:

1 The first group comprises methods that do not involve cost, for example, the proper use and ceaseless care of devices and equipment in milling.
2 The second group comprises methods that have costs, but these costs are not high (low cost methods), such as maintenance and repair of equipment, measuring energy consumption in different milling devices, monitoring the consumption of each device, implementing training programs on energy reduction methods.
3 The third group comprises costly methods. In these methods, fundamental changes must be made to improve energy consumption in devices and facilities, for example, in cases the devices are old, replacement by new devices or installation of additional devices to prevent energy loss.

Table 5
Energy indices of milling factories in Guilan province, Iran.

Items	Unit	Value
Energy ratio	–	0.17
Energy productivity	kg MJ^{-1}	0.01
Specific energy	MJ kg^{-1}	97.44
Net energy gain	MJ $1TIP^{-1}$	−56283.67

Table 6
Uncertainty analysis of inputs energy in milling factories in Guilan province, Iran.

Inputs	Normal standard deviation (S_n)		The cover surface percentage of normal distribution (%)		Uncertainty percentage (100-(A + B)) (%)
	Lower band	Upper band	Negative section (A)	Positive section (B)	
1. Human labor	1.53	1.32	43.57	40.66	15.77
2. Machinery	1.79	2.02	45.45	47.78	6.77
3. Electricity	0.66	0.81	24.54	29.1	46.36
4. Natural gas	0.65	0.74	24.22	27.04	48.74
5. Nylon	0.9	1.23	31.59	39.07	29.34
6. Transportation	1.31	1.41	40.49	41.92	17.59

Fig. 5 displays error bars of each input and total energy consumption. This chart is divided into tree section based on scales for better understanding. In other words, inputs with close amount are shown in each section.

3.2. LCA result interpretation

Results obtained from environmental analysis of milling factories are presented in this section, based on the following impact categories, namely, PO, TE, ME, FE, HT, OLD, GWP, EP, AC and AD. Amounts of impact categories listed per ton paddy of conversion to white rice are shown in Table 7.

The total GWP is calculated to be 8413.24 kg $CO_{2\ eq.}$ one per ton input paddy (5.88 kg $CO_{2\ eq.}$ per kg of milled and packed white rice). Hokazono and Hayashi (2012) reported an amount of 1.46 kg $CO_{2\ eq.}$ for each kg of milled brown rice in Japan under their conversion system. Brodt et al. (2014) reported net emissions during the life cycle of 1.47 kg $CO_{2\ eq.}$ for each kg of milled rice. GWP was 2.52–2.66 kg $CO_{2\ eq.}$ for each kg of milled and packed white rice (Beccali et al., 2009). Accordingly, the GWP rate in this study is about 2–4 times those of the above-mentioned studies. The main factor for this rising rates is the high consumption of natural gas in dryers. This is owing to the fact that Iran have large resources of natural gas and this fossil input with low price is provided to consumers. Therefore, low price and very easy access to natural gas lead to the lack of attention of unit managers to natural gas

Table 7
Environmental impacts of milling factories in Guilan province, Iran per FU.

Impact category	Measurement units	Emission rate
AD	kg $Sb_{eq.}$	4.12×10^1
AC	kg $SO_{2\ eq.}$	8.08
EP	kg $PO^{-3}{}_{4\ eq.}$	1.57
GWP	kg $CO_{2\ eq.}$	8.41×10^3
OLD	kg CFC11 $_{eq.}$	3.00×10^{-5}
HT	kg 1,4-DB $_{eq.}$	3.30×10^2
FE	kg 1,4-DB $_{eq.}$	1.05×10^2
ME	kg 1,4-DB $_{eq.}$	3.55×10^5
TE	kg 1,4-DB $_{eq.}$	8.50×10^{-1}
PO	kg $C_2H_{4\ eq.}$	1.10

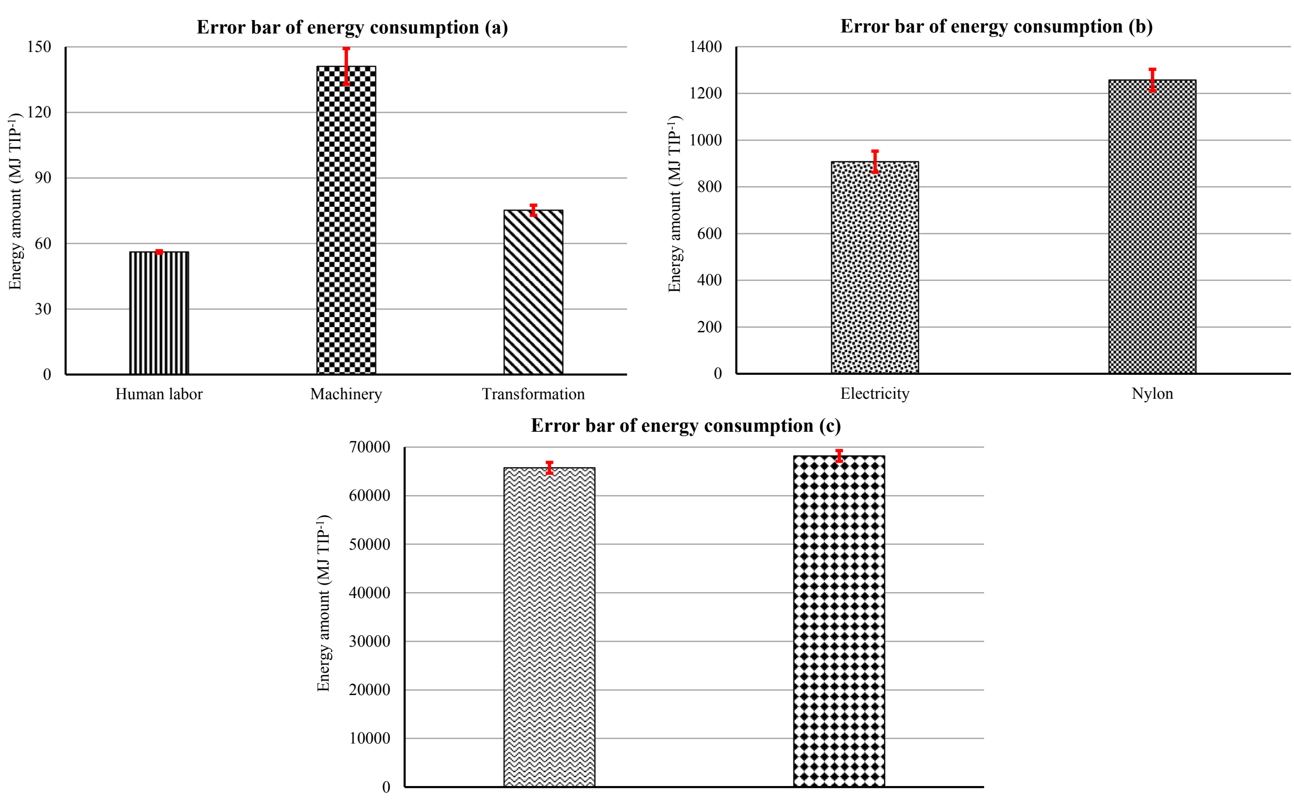

Fig. 5. Graphical display of error bars in energy consumption.

consumption. Eventually, since combustion of fossil fuels is one of the main factors in the phenomenon of global warming, carbon dioxide equivalent per kilogram of white rice has risen.

Fig. 6 indicates the environmental impact pattern in milling factories as well as the share of every input under different impact categories. It can be observed that natural gas (background processes of natural gas extraction and production) has the major share in impact categories of TE, OLD, AD, HT, FE and ME. On the other hand, AC, EP, GWP, and PO are heavily affected by emissions caused by combustion of natural gas at milling factories. Based on this, as discussed in the previous section, the change in the structure of the dryers in terms of increasing the efficiency of the machines, as well as changing the type of fuel can mitigate environmental damages of converting paddy to white rice.

3.3. CExD

Table 8 and Fig. 7 show results obtained from energy analysis according to CExD for 1 MJ $1TIP^{-1}$. It is found that 2310.40 (MJ $1TIP^{-1}$) of fossil energy consumption is undergone in the conversion process from paddy to white rice in milling factories. Nylon (background processes of nylon production) of packing has a share equal to 90% of non-renewable, fossil. It should be noted that many million tons of plastic are consumed in each year globally. Limitations should be imposed on employing recycled plastic in human food sector as far as possible, by replacing them with packaging substances having less environmental impact. Moreover, with the consumed plastics in this sector successfully recycled and employed in another sector, environmental impacts of background processes in that sector will be mitigated. Nucci et al. (2014) found that the energy consumption of the packaging step can be decreased by altering the packaging of the product, specifically by reducing the marital packaging weight. The major edconsum energy for categories of renewable, potential is related to electricity while that for renewable, water is related to industry equipment for whiting and packing of rice. According to Fig. 7, natural gas and nylon (background processes) have main shares in the non-renewable, metals and material, respectively. This result emphasizes on dryers and packaging to avoid non-renewable resources use.

Table 8
Results of energy forms computed by CExD method of LCA.

Items	Measurement units	Value
1. Non-renewable, fossil	MJ $1TIP^{-1}$	2310.40
2. Renewable, potential	MJ $1TIP^{-1}$	118.72
3. Renewable, water	MJ $1TIP^{-1}$	1547.08
4. Non-renewable, metals	MJ $1TIP^{-1}$	42.20
5. Non-renewable, minerals	MJ $1TIP^{-1}$	144.15

3.4. Economic analysis results

Table 9 shows that the total SC emissions (with electricity and natural gas) per ton of paddy for conversion to white rice in milling factories in Guilan province, Iran equals to 30.99 (\$ $1TIP^{-1}$). 84% of this is related to $SCCO_2$. Although the cost per unit of CO_2 is very low compared to other emissions (Table 3), yet because of its high emissions in natural gas and electricity consumption, this cost will be the main contribution to the total cost. $SCCO_2$ denotes a broad measure of climate change damages and covers changes in costs of energy system, such as elevated air conditioning costs and reduced heating costs, and changes in property loss, human health and agricultural productivity from elevated flood risk. Nevertheless, it does not cover all significant damages owing to current limitations on data and modeling. As shown in Table 3, for each cubic meter of natural gas consumed, the value of CO_2 emission is 1.9292 kg CO_2 $_{eq.}$, so the saving per cubic meter will prevent the release of 1.9292 kg $_{eq.}$, which is equivalent to 0.01 \$. This result also emphasizes the change in the structure and type of fuel used by dryers in milling factories.

In order to evaluate the milling factories and conversion of paddy to white rice, analysis is undertaken from economic point of view with results given in Table 10. By multiplying the rice yield with the sale price, total conversion of paddy to white rice revenue is computed as 341.58 (\$ $1TIP^{-1}$) (Table 10). The fixed and variable costs are computed to be 94.15 and 200.06 (\$ $1TIP^{-1}$), accounting for 32% and 68% of the total cost, respectively while, based on another research in paddy farm, the fixed and variable costs were 22% and 78% of the total cost, respectively (Pishgar-Komleh et al., 2011). This result shows the greater share of variable costs in converting paddy to white rice due to consumption of inputs such

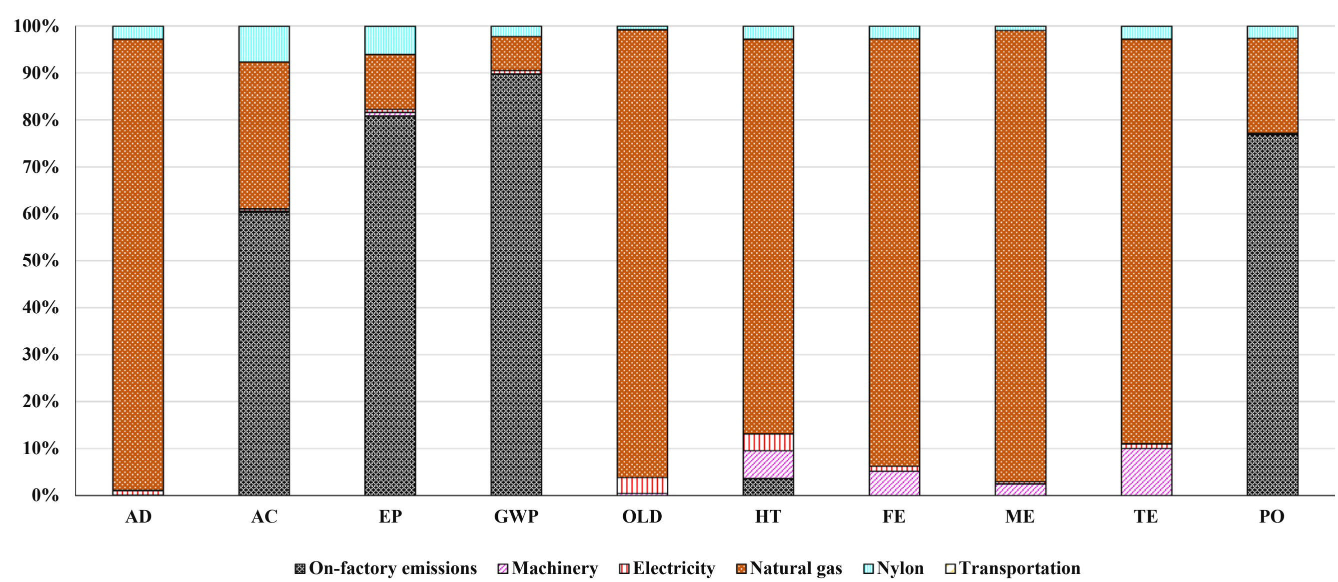

Fig. 6. Contribution of inputs to environmental impact categories for white rice production in milling factories.

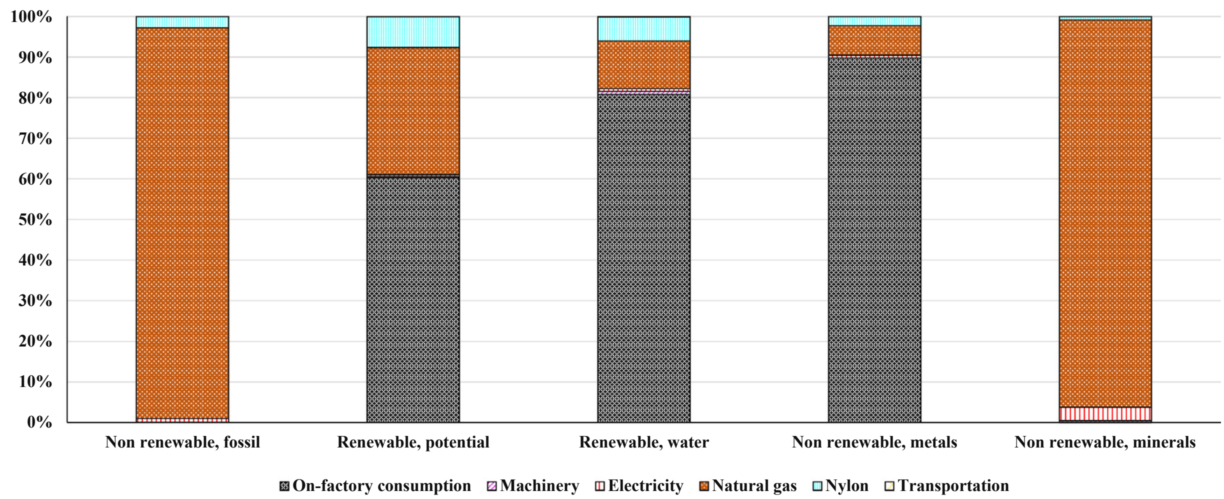

Fig. 7. Contribution of inputs to consumption of energy forms in for white rice production in milling factories based on CExD.

Table 9
Social cost of background emissions for milling factories in Guilan province, Iran.

Items	Unit	Cost
1. NO_X cost	\$ $1TIP^{-1}$	3.03
2. SO_2 cost	\$ $1TIP^{-1}$	0.44
3. CO cost	\$ $1TIP^{-1}$	0.18
4. SPM cost	\$ $1TIP^{-1}$	1.12
5. CO_2 cost	\$ $1TIP^{-1}$	26.17
6. CH_4 cost	\$ $1TIP^{-1}$	0.04
7. N_2O cost	\$ $1TIP^{-1}$	0.02
Total emission cost	\$ $1TIP^{-1}$	30.99

as fuel, electricity, etc. At the end of economic analysis of converting paddy to white rice, the average net profit is computed to be 47.37 (\$ $1TIP^{-1}$), which is about 19% of the proceeds from the sale of white rice. This profit will greatly increase with decreasing input consumption through optimized consumption, especially in relation to the consumption of natural gas for dryers. In order to determine the amount of saved natural gas with the current conditions (without changing the system of dryers or the type of fuel used) without reducing the yield of white rice, optimize methods such as Data Envelopment Analysis (DEA) can be used. Besides, changing of drying system can also reduce energy consumption by about 40%, as mentioned above. In the next step, by replacing the consumption of natural gas with clean and stable energies, much more natural gas can be stored. However, as long as sustainable energies are not commercially and economically used and given the specific climate of the region in the study area, natural gas cannot be completely abandoned.

3.5. Multi-level ANFIS models

Programs written in MATLAB are run to identify the best combination of variables in ANFIS model with the highest accuracy. In this study, to have the best model for prediction of GWP, economic profit and energy, linear membership function is adopted at the output layer for the two level ANFIS model among different membership functions including Q-shaped generalized bell, Gaussian combination, Gaussian curve, generalized bell, trapezoidal, and triangular, membership functions. Moreover, 32 epochs are used to train the model with the specified input-output relationships so as to determine the optimized MF distribution in accordance with the hybrid learning method. Least square method is used for parameters independent of output MF whilst backpropagation algorithm is used for parameter independent of input MF and (Singh et al., 2012). This learning algorithm was chosen in various previous works with high success, for example: modeling egg production with hybrid learning method and attaining appropriate results (Sefeedpari et al., 2016). In the followings, modeling results are presented separately for prediction of energy, economic profit and GWP.

Table 10
Economic analysis of milling factories in Guilan province, Iran.

Items (unit)	Average
Sales price (\$ kg)	3.25
Total production revenue (\$ 1TIP-1)	341.58
Variable cost of production (\$ $1TIP^{-1}$)	200.06
Fixed cost of production (\$ $1TIP^{-1}$)	94.15
Total cost of production (\$ $1TIP^{-1}$)	294.21
Net profit (\$ $1TIP^{-1}$)	47.37

3.5.1. ANFIS models for computing output energy

The correlation of observed values and predicted values of output energy (yield) by ANFIS (1) to (4) in converting paddy to white rice in milling factories is shown in Fig. 8. Based on Fig. 4, ANFIS (1), with the first level made up of input variables of machinery energy and human labor, R^2 value between predicted and observed output energy is computed to be 0.811 (Fig. 8a). Moreover, Fig. 8b shows that the corresponding R^2 value for input variables of natural gas and electricity (ANFIS (2)) equal to 0.156 (less R^2 means that the change in natural gas and electricity consumption correlate slightly with the yield of white rice. Therefore, the decrease in their value does not lead to yield decline. Hence, due to their high consumption, especially natural gas, they can be easily saved without leading to a loss of yield). In the first level of ANFIS, R^2 value for ANFIS (3) (based on Fig. 4, predicted output energy from nylon and transportation) is 0.484 (Fig. 8c). In the second ANFIS level (Fig. 4), outputs deriving from ANFIS (1), ANFIS (2) and ANFIS (3) become input variables of ANFIS (4). Based on this, the R^2 value is shown as 0.911, indicating the high accuracy of the ANFIS (4) in predicting the output energy in milling factories.

Table 11 summarizes statistical parameters in predicting output energy by the two level ANFIS topology. It can be observed that ANFIS adopting Gbell MFs for input layer and linear MF for output layers is the best combination. Besides, error analysis results are

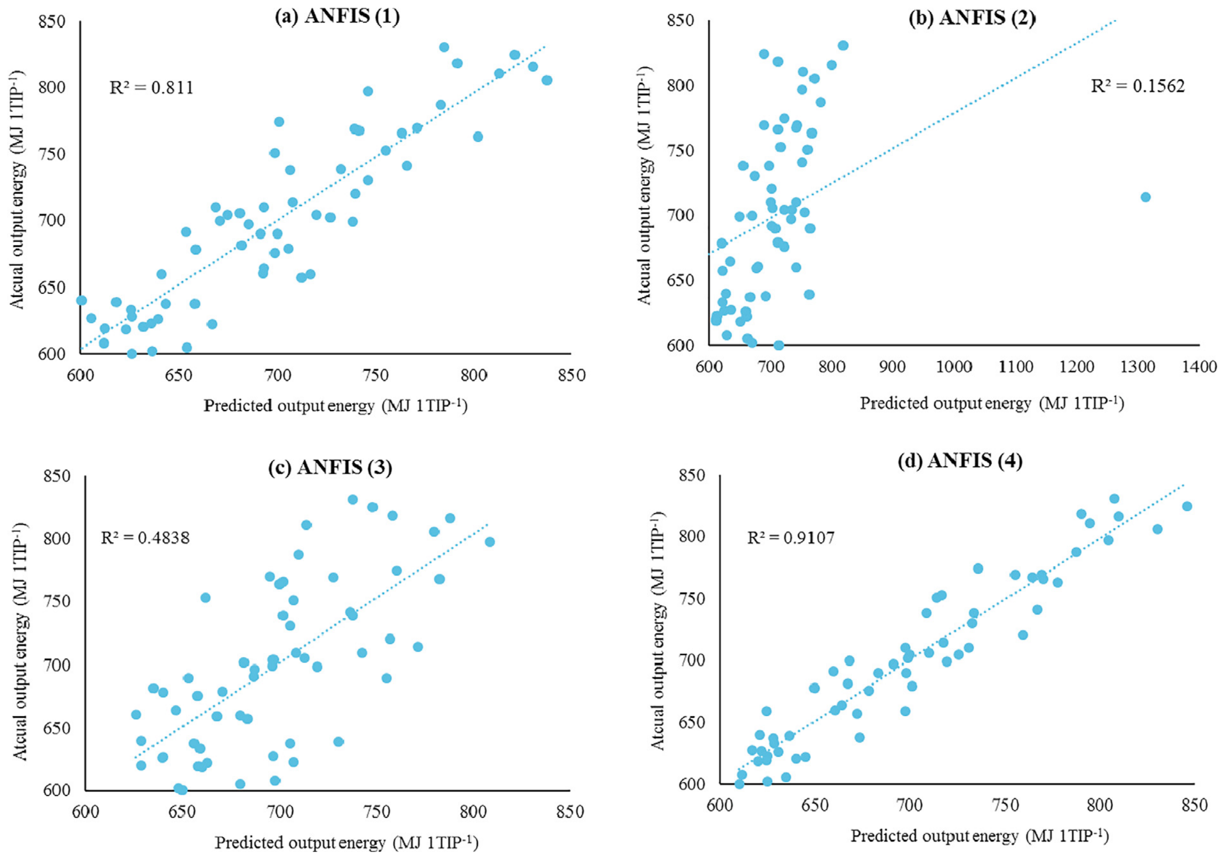

Fig. 8. Cross-correlation of predicted and observed values for energy output of white rice production in milling factories.

shown between forecasted and observed values of output energy of milling factories by employing the two-level ANFIS. For the first level ANFIS models, RMSE varies between 28.43 (MJ $1TIP^{-1}$) and 91.88 (MJ $1TIP^{-1}$); while in the second level it decreases to 19.49 (MJ $1TIP^{-1}$). For the final ANFIS model, MAE is 0.22, which indicates the excellent modeling power of the two-level ANFIS. The excellent power of multilayer ANFIS in modeling energy output were also shown for energy output (Sefeedpari et al., 2016) and canola production (Mousavi-Avval et al., 2017).

3.5.2. ANFIS models for assessing environmental impacts

The correlation between predicted values by ANFIS and observed values for GWP of packed white rice is shown in Fig. 9. In the first level of ANFIS, R^2 value between forecasted and observed values of GWP for input variables of machinery and human labor is 0.728 while R^2 values for ANFIS (2) (predicted GWP by natural gas and electricity) and ANFIS (3) (predicted GWP by nylon and transportation) in the first level of ANFIS are 0.914 and 0.527, respectively. Considering these three ANFIS as inputs for the fourth ANFIS in the second layer, R^2 value for real and predicted values for GWP is computed to be 0.982. This indicates that the two-level ANFIS structure is able to easily and precisely model GWP rates based on input energies in milling factories.

Table 12 summarizes results correlating ANFIS topology in modeling GWP rates in milling factories to input energies. RMSE for the first-level ANFIS are from 1057.24 to 451.15 (kg $CO_{2\ eq.}$ $1TIP^{-1}$) while in the second-level, this value decreases to 291.86. Moreover, MAE for ANFIS (1) to (4) varies from 0.77 to 0.29, respectively. This result shows high accuracy of the model in the second layer.

3.5.3. ANFIS models for evaluating economic profit

The correlation between forecasted values by ANFIS and observed values for economic profit of milling factories is shown in Fig. 10. According to the two levels of ANFIS and Fig. 10a, the R^2 value for real values and predicted values related to machinery and human labor is found to be 0.864. As seen in Fig. 10b, R^2 value for ANFIS (2) (predicted economic profit by natural gas and electricity) is 0.922. The coefficient of determination for ANFIS (3) (denoting forecasted economic profit from nylon and transportation) in the first level of ANFIS is 0.661 (Fig. 10c). In the second ANFIS level,

Table 11
Characteristics of the best structure of the first ANFIS architecture for prediction of output energy of milling factories based on 1TIP by applying two-level ANFIS.

ANFIS model	Type of MF		Number of MF		Learning method	RMSE (MJ $1TIP^{-1}$)	R^2	MAE
	Input	Output	Input	Epoch				
ANFIS (1)	Gbell	Linear	2,3	32	Hybrid	28.43	0.811	0.33
ANFIS (2)	Gbell	Linear	2,3	32	Hybrid	91.88	0.156	0.63
ANFIS (3)	Gbell	Linear	2,3	32	Hybrid	46.82	0.484	0.54
ANFIS (4)	Gbell	Linear	2,3	32	Hybrid	19.49	0.911	0.22

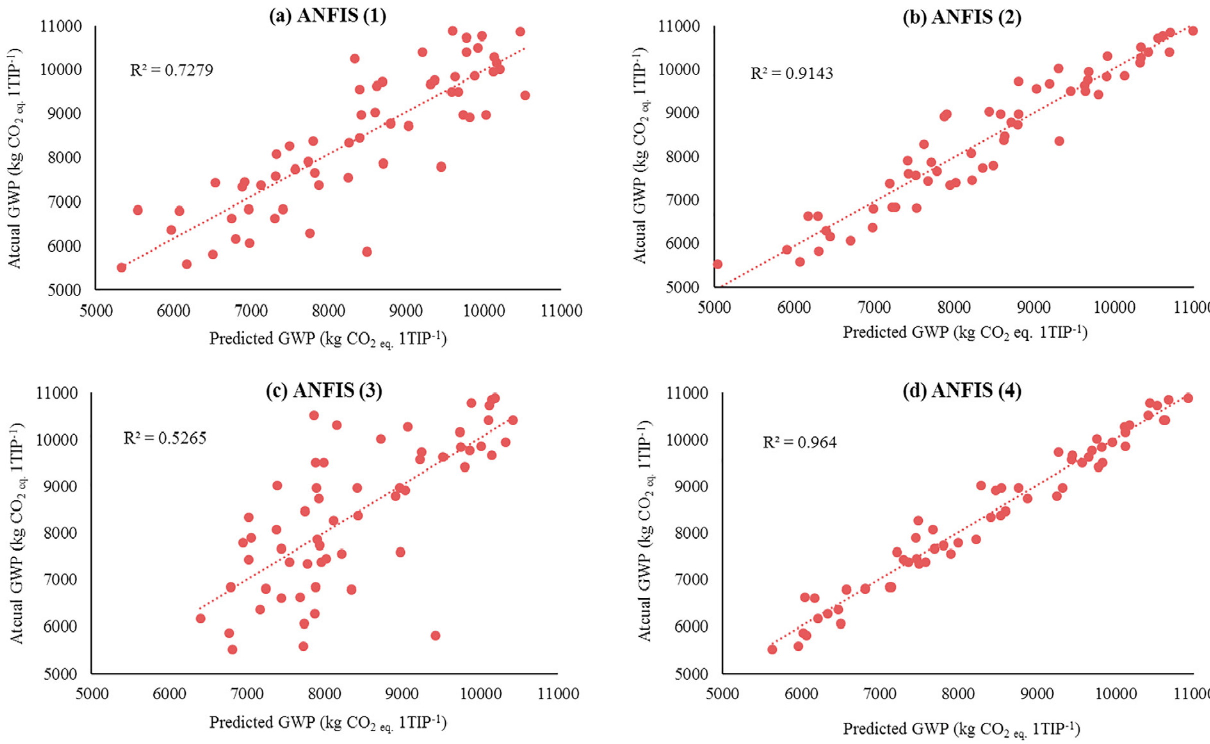

Fig. 9. Cross-correlation of predicted and observed values for GWP of white rice production in milling factories.

Table 12
Characteristics of the best structure of the first ANFIS architecture for prediction of GWP of milling factories based on 1TIP by applying two-level ANFIS.

ANFIS model	Type of MF		Number of MF		Learning method	RMSE (kg CO_2 $_{eq.}$ $1TIP^{-1}$)	R^2	MAE
	Input	Output	Input	Epoch				
ANFIS (1)	Gbell	Linear	2,3	32	Hybrid	805.21	0.728	0.77
ANFIS (2)	Gbell	Linear	2,3	32	Hybrid	451.15	0.914	0.45
ANFIS (3)	Gbell	Linear	2,3	32	Hybrid	1057.24	0.527	0.97
ANFIS (4)	Gbell	Linear	2,3	32	Hybrid	291.86	0.964	0.29

outputs of ANFIS (1), ANFIS (2) and ANFIS (3) are selected as inputs to ANFIS (4). Results show that the correlation R^2 between the predicted and observed economic profits is 0.978 (Fig. 10d). A high R^2 for ANFIS (4) indicates high model accuracy in predicting economic profit in milling factories.

Table 13 presents results of some statistical parameters by comparison between real and predicted economic profit amount, based on the two-level ANFIS. It shows that the adoption of Gbell MF for input layer and linear MF output layer lead to the selected model for forecasting economic profit. As shown in Table 13, for the first level ANFIS models, RMSE varies from 0.31 to 0.36 whilst, for second level, the corresponding value is from 19.42 to 30.77 ($ $1TIP^{-1}$) and in the second level it reduces to 7.88 ($ $1TIP^{-1}$). Besides, MAE for the selected ANFIS model decreases from 8.80 by ANFIS (2) in the first level to 0.5 by ANFIS (4) in the second level. Results indicate the high power of the two-layer ANFIS to predict economic profit in milling factories.

4. Conclusions

This study aims to assess life and energy cycles of white rice in milling factories of Guilan province, Iran. The considered boundary system includes the transportation of paddy to the factory to packing by nylon at the end. The energy input is computed to be 68,178.31 (MJ $1TIP^{-1}$). In milling factories, most energy is consumed by natural gas (96.43%) while nylon (1.84%) in the milling factories is in the second place. Hence, natural gas has the most important role in energy consumption. Because this amount of natural gas is used in dryers, the use of dryers with higher efficiency or the shift of fuel to renewable fuels such as solar and biomass is necessary. In conversion paddy to white rice, the energy ratio is computed to be 0.17, which shows low energy efficiency in milling factories. Results of LCA indicate that converting paddy to white rice in milling factories results in emission of 8413.24 kg CO_2 $_{eq.}$ However, the change in the type of fuel consumed, followed by decreasing GHG emissions as results of combustion of clean fuels (biogas, biodiesel, etc.), can reduce GWP rate since natural gas or methane is seventy-two times more capable than carbon dioxide in retaining heat within atmosphere for a period of 20 years after being released. Methane is worst in the short term since it gradually converts to carbon dioxide. The GWP is about 25 times that of carbon dioxide over 100 years. Besides, results show that the total SC emissions (with electricity and natural gas) per ton of paddy for conversion to white rice chain in milling factories in Guilan province, Iran equal to 30.99 ($ $1TIP^{-1}$) and 84% this is related to $SCCO_2$. The average economic profit is computed to be 47.37 ($ $1TIP^{-1}$) which is about 19% of the proceeds from the sale of white rice.

Results of implementation of multi-level ANFIS reveal that, two-level ANFIS architecture comprising of three ANFIS models in the first level and one ultimate model in the third level attains the best

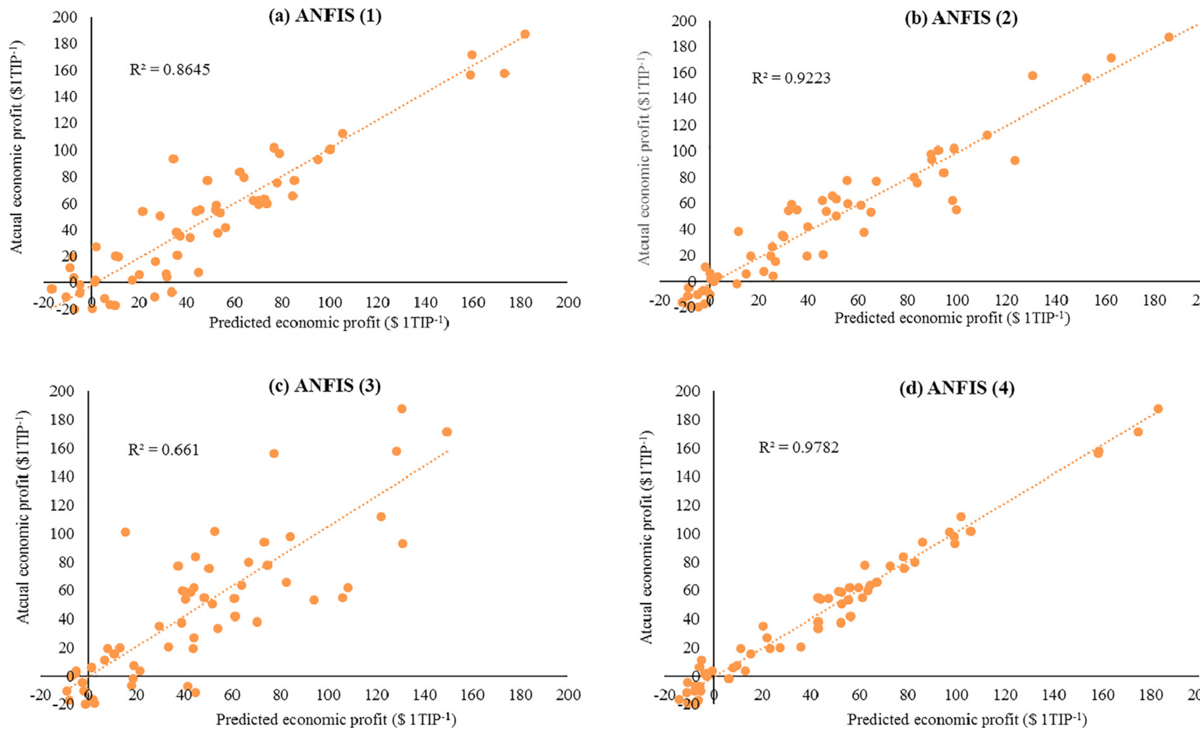

Fig. 10. Cross-correlation of predicted and observed values for economic profit of white rice production in milling factories.

Table 13
Characteristics of the best structure of the first ANFIS architecture for prediction of profit of milling factories based on 1TIP by applying two-level ANFIS.

ANFIS model	Type of MF		Number of MF		Learning method	RMSE ($ $1TIP^{-1}$)	R^2	MAE
	Input	Output	Input	Epoch				
ANFIS (1)	Gbell	Linear	2,3	32	Hybrid	19.42	0.864	2.27
ANFIS (2)	Gbell	Linear	2,3	32	Hybrid	14.71	0.922	8.80
ANFIS (3)	Gbell	Linear	2,3	32	Hybrid	30.77	0.661	1.48
ANFIS (4)	Gbell	Linear	2,3	32	Hybrid	7.83	0.978	0.50

forecasting performance for output energy, economic profit and GWP for converting paddy to white rice. In addition to computing the quantity of converting paddy to white rice and mitigating adverse environmental factors, model prediction results in lower costs. This is because it can easily predict how many white rice are produced per input and how much pollution are generated and, with this knowledge, it will determine where the revenue from white rice is less than the cost of converting paddy to white rice as well as the cost of combating environmental pollution. Apart from reducing the total cost, this model is able to deal directly with environmental crises and avoid any delay in employing the contemporary techniques.

Acknowledgements

We gratefully acknowledge the financial support provided by Department of Agricultural Machinery Engineering, Faculty of Agricultural Engineering and Technology, University of Tehran, Karaj, Iran. Moreover, the first author would like to express his gratitude to Ms. Fatemeh Hosseini-Fashami for her helpful suggestions in revision process.

References

Arzoumanidis, I., Salomone, R., Petti, L., Mondello, G., Raggi, A., 2017. Is there a simplified LCA tool suitable for the agri-food industry? An assessment of selected tools. J. Clean. Prod. 149, 406–425.
Beccali, M., Cellura, M., Iudicello, M., Mistretta, M., 2009. Resource consumption and environmental impacts of the agrofood sector: life cycle assessment of Italian citrus-based products. Environ. Manag. 43, 707–724.
Bland, J.M., Altman, D.G., 1996. Statistics notes: measurement error. BMJ 312, 1654.
Blengini, G.A., Busto, M., 2009. The life cycle of rice: LCA of alternative agri-food chain management systems in Vercelli (Italy). J. Environ. Manag. 90, 1512–1522.
Bösch, M.E., Hellweg, S., Huijbregts, M.A.J., Frischknecht, R., 2007. Applying cumulative exergy demand (CExD) indicators to the ecoinvent database. Int. J. Life Cycle Assess. 12, 181.
Brodt, S., Kendall, A., Mohammadi, Y., Arslan, A., Yuan, J., Lee, I.-S., Linquist, B., 2014. Life cycle greenhouse gas emissions in California rice production. Field Crop. Res. 169, 89–98.
Canakci, M., Akinci, I., 2006. Energy use pattern analyses of greenhouse vegetable production. Energy 31, 1243–1256.
Chauhan, M.K., Varun Chaudhary, S., Kumar, S., Samar, 2011. Life cycle assessment of sugar industry: a review. Renew. Sustain. Energy Rev. 15, 3445–3453.
Chen, X., Chau, K., Wang, W., 2015. A novel hybrid neural network based on continuity equation and fuzzy pattern-recognition for downstream daily river discharge forecasting. J. hydroinformatics 17, 733–744.
Cochran, W.G., 1977. The estimation of sample size. Sampl. Tech. 3, 72–90.
Ecoinvent Database, 2013. Ecoinvent database. http://www.ecoinvent.org/,_Version_3.3.
European Commission, 2010. ILCD Handbook-General Guide for Life Cycle Assessment-Detailed Guidance. European Commission, Joint Research Centre, Institute for Environment and Sustainability. Publications Office of the European Union, Luxembourg.
FAO, 2014. The State of Food Insecurity in the World. Food and Agriculture Organization. http://www.fao.org/.
Firouzi, S., Alizadeh, M.R., Haghtalab, D., 2017. Energy consumption and rice milling quality upon drying paddy with a newly-designed horizontal rotary dryer. Energy 119, 629–636.

Foley, D.K., Rezai, A., Taylor, L., 2013. The social cost of carbon emissions: seven propositions. Econ. Lett. 121, 90–97.
Gibon, T., Wood, R., Arvesen, A., Bergesen, J.D., Suh, S., Hertwich, E.G., 2015. A methodology for integrated, multiregional life cycle assessment scenarios under large-scale technological change. Environ. Sci. Technol. 49, 11218–11226.
Goyal, S.K., Jogdand, S.V., Agrawal, A.K., 2008. A study of energy audit in rice processing machines. Progress. Agric. 8, 34–38.
Guinée, J., 2001. Handbook on life cycle assessment-operational guide to the ISO standards. Int. J. Life Cycle Assess. 6, 255.
Guinée, J.B., 2002. Handbook on life cycle assessment operational guide to the ISO standards. Int. J. Life Cycle Assess. 7, 311.
Heijungs, R., Guinée, J.B., Huppes, G., Lankreijer, R.M., Udo de Haes, H.A., Wegener Sleeswijk, A., Ansems, A.M.M., Eggels, P.G., Duin, R., van, De Goede, H.P., 1992. Environmental Life Cycle Assessment of Products: Guide and Backgrounds (Part 1). CML, Leiden.
Hokazono, S., Hayashi, K., 2012. Variability in environmental impacts during conversion from conventional to organic farming: a comparison among three rice production systems in Japan. J. Clean. Prod. 28, 101–112.
Hosseinzadeh-Bandbafha, H., Nabavi-Pelesaraei, A., Khanali, M., Ghahderijani, M., Chau, K., 2018. Application of data envelopment analysis approach for optimization of energy use and reduction of greenhouse gas emission in peanut production of Iran. J. Clean. Prod. 172, 1327–1335.
ISO, 2006. 14040 International Standard. Environmental Management–Life Cycle Assessment–Principles and Framework. International Organisation for Standardization, Geneva, Switzerland.
Jafari, H., Kalantari, D., Azadbakht, M., 2018. Energy consumption and qualitative evaluation of a continuous band microwave dryer for rice paddy drying. Energy 142, 647–654.
Jalali-Sefat, M., 2013. Energy Economics Study of Jam Production in Razavi Khorasan Province. Faculty of Agriculture. University of Tabriz. M.Sc Thesis.
Jang, J.S., 1993. ANFIS: adaptive-network-based fuzzy inference system. IEEE Trans. Syst. Man. Cybern. 23, 665–685.
Jolliet, O., Margni, M., Charles, R., Humbert, S., Payet, J., Rebitzer, G., Rosenbaum, R., 2003. IMPACT 2002+: a new life cycle impact assessment methodology. Int. J. Life Cycle Assess. 8, 324.
Karkevandi-Talkhooncheh, A., Hajirezaie, S., Hemmati-Sarapardeh, A., Husein, M.M., Karan, K., Sharifi, M., 2017. Application of adaptive neuro fuzzy interface system optimized with evolutionary algorithms for modeling CO 2-crude oil minimum miscibility pressure. Fuel 205, 34–45.
Kasmaprapruet, S., Paengjuntuek, W., Saikhwan, P., Phungrassami, H., 2009. Life cycle assessment of milled rice production: case study in Thailand. Eur. J. Sci. Res. 30, 195–203.
Kostowski, W.J., Usón, S., Stanek, W., Bargiel, P., 2014. Thermoecological cost of electricity production in the natural gas pressure reduction process. Energy 76, 10–18.
Kucukvar, M., Egilmez, G., Tatari, O., 2014. Sustainability assessment of US final consumption and investments: triple-bottom-line input-output analysis. J. Clean. Prod. 81, 234–243.
Kumar, A., Priyadarshinee, R., Roy, A., Dasgupta, D., Mandal, T., 2016. Current techniques in rice mill effluent treatment: emerging opportunities for waste reuse and waste-to-energy conversion. Chemosphere 164, 404–412.
Kylili, A., Christoforou, E., Fokaides, P.A., 2016. Environmental evaluation of biomass pelleting using life cycle assessment. Biomass Bioenergy 84, 107–117.
Mandal, S., Roy, S., Das, A., Ramkrushna, G.I., Lal, R., Verma, B.C., Kumar, A., Singh, R.K., Layek, J., 2015. Energy efficiency and economics of rice cultivation systems under subtropical Eastern Himalaya. Energy Sustain. Dev. 28, 115–121.
Ministry of Energy of the Islamic Republic of Iran, 2012. Balance sheet of energy year 1390 (in Persian). www.moe.gov.ir.
Mousavi-Avval, S.H., Rafiee, S., Jafari, A., Mohammadi, A., 2011. Optimization of energy consumption for soybean production using Data Envelopment Analysis (DEA) approach. Appl. Energy 88, 3765–3772.
Mousavi-Avval, S.H., Rafiee, S., Sharifi, M., Hosseinpour, S., Shah, A., 2017. Combined application of life cycle assessment and adaptive neuro-fuzzy inference system for modeling energy and environmental emissions of oilseed production. Renew. Sustain. Energy Rev. 78, 807–820.
Mustayen, A., Mekhilef, S., Saidur, R., 2014. Performance study of different solar dryers: a review. Renew. Sustain. Energy Rev. 34, 463–470.
Nabavi-Pelesaraei, A., Abdi, R., Rafiee, S., Taromi, K., 2014. Applying data envelopment analysis approach to improve energy efficiency and reduce greenhouse gas emission of rice production. Eng. Agric. Environ. Food 7, 155–162.
Nabavi-Pelesaraei, A., Rafiee, S., Mohtasebi, S.S., Hosseinzadeh-Bandbafha, H., Chau, K., 2017. Energy consumption enhancement and environmental life cycle assessment in paddy production using optimization techniques. J. Clean. Prod. 162, 571–586.
Nabavi-Pelesaraei, A., Abdi, R., Rafiee, S., Shamshirband, S., Yousefinejad-Ostadkelayeh, M., 2016. Resource management in cropping systems using artificial intelligence techniques: a case study of orange orchards in north of Iran. Stoch. Environ. Res. Risk Assess. 30, 413–427.
Naji, S., Shamshirband, S., Basser, H., Keivani, A., Alengaram, U.J., Jumaat, M.Z., Petkovi, D., 2016. Application of adaptive neuro-fuzzy methodology for estimating building energy consumption. Renew. Sustain. Energy Rev. 53, 1520–1528.
Nikravesh, M., Zadeh, L.A., Aminzadeh, F., 2003. Soft Computing and Intelligent Data Analysis in Oil Exploration. Elsevier.
Nimmol, C., Devahastin, S., 2010. Evaluation of performance and energy consumption of an impinging stream dryer for paddy. Appl. Therm. Eng. 30, 2204–2212.
Nucci, B., Puccini, M., Pelagagge, L., Vitolo, S., Nicolella, C., 2014. Improving the environmental performance of vegetable oil processing through LCA. J. Clean. Prod. 64, 310–322.
Paté-Cornell, E.M., 1996. Uncertainties in risk analysis: six levels of treatment. Reliab. Eng. Syst. Saf. 54, 95–111.
Peters, J.F., Petrakopoulou, F., Dufour, J., 2014. Exergetic analysis of a fast pyrolysis process for bio-oil production. Fuel Process. Technol. 119, 245–255.
Pishgar-Komleh, S.H., Sefeedpari, P., Rafiee, S., 2011. Energy and economic analysis of rice production under different farm levels in Guilan province of Iran. Energy 36, 5824–5831.
Qasemi-Kordkheili, P., Nabavi-Pelesaraei, A., 2014. Optimization of energy required and potential of greenhouse gas emissions reductions for nectarine production using data envelopment analysis approach. Int. J. Energy Environ. 5, 207–218.
Quispe, I., Navia, R., Kahhat, R., 2017. Energy potential from rice husk through direct combustion and fast pyrolysis: a review. Waste Manag. 59, 200–210.
Rocco, M.V., Colombo, E., Sciubba, E., 2014. Advances in exergy analysis: a novel assessment of the Extended Exergy Accounting method. Appl. Energy 113, 1405–1420.
Roomi, M.S.M., Namal, D.D.A., Jayasinghe, K.T., 2007. Study of energy consumption pattern in Sri Lankan rice mills-enhancing opportunity for conservation. Eng. J. Inst. Eng. Sri Lanka 40.
Roy, P., Ijiri, T., Nei, D., Orikasa, T., Okadome, H., Nakamura, N., Shiina, T., 2009. Life cycle inventory (LCI) of different forms of rice consumed in households in Japan. J. Food Eng. 91, 49–55.
Roy, P., Shimizu, N., Kimura, T., 2005. Life cycle inventory analysis of rice produced by local processes. J. Japanese Soc. Agric. Mach. 67, 61–67.
Sabzevari, A., Kouchaki-Penchah, H., Nabavi-Pelesaraei, A., 2015. Investigation of life cycle assessment of hazelnut production in Guilan province of IR Iran based on orchards size levels. Bio. Forum 7, 807–813.
Safari, H., Nekoeian, S., Shirdel, M.R., Ahmadi, H., Bahadori, A., Zendehboudi, S., 2014. Assessing the dynamic viscosity of Na–K–Ca–Cl–H2O aqueous solutions at high-pressure and high-temperature conditions. Ind. Eng. Chem. Res. 53, 11488–11500.
Sangdao, C., Songsermpong, S., Krairiksh, M., 2010. A continuous fluidized bed microwave paddy drying system using applicators with perpendicular slots on a concentric cylindrical cavity. Dry. Technol. 29, 35–46.
Sarker, M.S.H., Ibrahim, M.N., Aziz, N.A., Salleh, P.M., 2014. Energy and rice quality aspects during drying of freshly harvested paddy with industrial inclined bed dryer. Energy Convers. Manag. 77, 389–395.
Sefeedpari, P., Rafiee, S., Akram, A., Chau, K., Pishgar-Komleh, S.H., 2016. Prophesying egg production based on energy consumption using multi-layered adaptive neural fuzzy inference system approach. Comput. Electron. Agric. 131, 10–19.
Silalertruksa, T., Gheewala, S.H., 2013. A comparative LCA of rice straw utilization for fuels and fertilizer in Thailand. Bioresour. Technol. 150, 412–419.
Singh, R., Kainthola, A., Singh, T.N., 2012. Estimation of elastic constant of rocks using an ANFIS approach. Appl. Soft Comput. 12, 40–45.
Stoellinger, T., Righetti, T., Coddington, K., 2016. Impact of social cost of carbon analyses in the development of energy projects on federal land. Electr. J. 29, 63–70.
Suganthi, L., Samuel, A.A., 2012. Energy models for demand forecasting-A review. Renew. Sustain. Energy Rev. 16, 1223–1240.
Taheri-Rad, A., Khojastehpour, M., Rohani, A., Khoramdel, S., Nikkhah, A., 2017. Energy flow modeling and predicting the yield of Iranian paddy cultivars using artificial neural networks. Energy 135, 405–412.
Thanawong, K., Perret, S.R., Basset-Mens, C., 2014. Eco-efficiency of paddy rice production in Northeastern Thailand: a comparison of rain-fed and irrigated cropping systems. J. Clean. Prod. 73, 204–217.
Van den Bergh, J., Botzen, W.J.W., 2015. Monetary valuation of the social cost of CO 2 emissions: a critical survey. Ecol. Econ. 114, 33–46.
Xu, Y., Szmerekovsky, J., 2017. System dynamic modeling of energy savings in the US food industry. J. Clean. Prod. 165, 13–26.
Yousefinejad-Ostadkelayeh, M., 2015. Evaluation of Energy Consumption and Emissions from Main Cigarette Production Factories in Iran. Faculty of Agricultural Engineering and Technology (M.Sc thesis). University of Tehran.
Yu, S., Wei, Y.-M., Wang, K., 2012. A PSO-GA optimal model to estimate primary energy demand of China. Energy Policy 42, 329–340.
Zecchi, B., Gerla, P., 2007. Breakage and mass transfer models during drying of rough rice. Dry. Technol. 25, 1405–1410.